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Smartphones get emotional: mind reading images and reconstructing the neural sources

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Abstract. Combining a 14 channel neuroheadset with a smartphone to capture and process brain imaging data, we demonstrate the ability to distinguish among emotional responses reflected in different scalp potentials when viewing pleasant and unpleasant pictures compared to neutral content. Clustering independent components across subjects we are able to remove artifacts and identify common sources of synchronous brain activity, consistent with earlier findings based on conventional EEG equipment. Applying a Bayesian approach to reconstruct the neural sources not only facilitates differentiation of emotional responses but may also provide an intuitive interface for interacting with a 3D rendered model of brain activity. Integrating a wireless EEG set with a smartphone thus offers completely new opportunities for modeling the mental state of users as well as providing a basis for novel bio-feedback applications.

Keywords: affective computing, mobile EEG, ICA clustering, source reconstruction

1 Motivation

Consciousness and emotion are not separable. Cognitively speaking our feelings can be thought of as labels that we consciously assign to the emotional responses triggered by what we perceive [1]. While we often think of affective terms as describing widely different states, these can be represented as related components in a circumplex model framed by the two psychological primitives: valence and arousal [2]. Related to viewing affective pictures, earlier neuroimaging studies have established that emotional content trigger not only autonomic responses of increased heart rate and electrodermal skin conductance, but also distinct brain potentials characterizing pleasant or unpleasant feelings compared to neutral imagery [3]. These ERP responses covary with both autonomic arousal and self report [4], and have been validated by affective user ratings in the IAPS set of affective pictures, using the psychological dimensions of valence and arousal to define how pleasant or intense the emotional content is perceived as being [5]. Previous brain imaging studies of emotional responses when viewing affective pictures [4] have identified distinct differences in the ERP amplitudes elicited

by pleasant and unpleasant compared to neutral images. An early component emerge most pronounced for pleasant content at 150-200ms termed early posterior negativity EPN, triggering a relative negative shift over temporal occipital areas and a positive potential over central sites [6]. Followed by yet another ERP component; a late positive potential LPP at 300-500ms, characterized by an enhanced posterior positivity over central parietal sites for affective compared to neutral content, with left hemisphere enhanced for pleasant pictures while activation appeared right lateralized for unpleasant images [3].

Only recently affordable wireless EEG headsets, initially designed as cognitive game interfaces have become available, and subsequently been applied as brain machine interfaces to directly manipulate robotic arms [7], drive a car [8] or mentally select images using the P300 oddball paradigm to call contacts by mentally selecting their image from the phonebook of an iPhone [9]. Scott Makeig et al. [10] have summarized the many benefits of brain monitoring under naturalistic conditions, emphasizing the need for going beyond brain imaging paradigms gauging how a few bits of information move through the brain when tapping a finger, and widen the focus to map out how we actively perceive our surroundings in a mobile context reflected in embodied cognition and real life emotional responses. However the obvious question remains whether the limited number of electrodes and the quality of consumer priced EEG sets make it feasible to capture brain imaging data in noisy environments. We therefore decided to combine a wireless neuroheadset with a smartphone for presenting media, gauge the emotional responses by capturing the EEG data and subsequently process and visualize the reconstructed patterns of brain activity on the device. And in the following sections outline the mobile EEG system design, experimental setup, results based on ICA analysis and source reconstruction, which are discussed in relation to earlier neuroimaging findings obtained in laboratory settings using conventional EEG equipment.

2 Methods

2.1 Mobile EEG system

The Neuroheadset transmits the EEG and control data to a receiver module with a standard USB connector, originally intended for a Windows PC running the Emotiv research edition SDK. We instead connect the receiver module directly to the USB port on a Nokia N900 smartphone, running Maemo 5. The current version is designed as a client-server architecture so that computationally expensive data analysis can be performed on a remote server and results are transmitted back to the phone for presentation. For synchronizing the stimuli with the captured EEG data, we timestamp the beginning and end of the recording when the first and last packets arrive. Meaning, the theoretical 128 Hz sample rate turns out to be 126-127 Hz when averaged over several minutes of recording. The timestamps saved during the experiments indicate that a resolution of 10 msec is achieved with the current Python implementation.

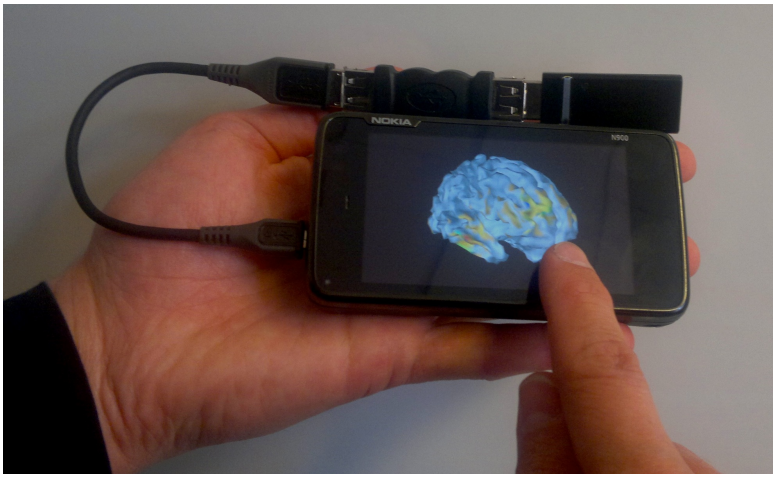

Fig. 1. The wireless 14 channel neuroheadset transmits the brain imaging data via a receiver connected directly to the USB port on a Nokia N900 smartphone, using components and custom-made software in order to transfer the received EEG data to a server for further processing. The present implementation allows interaction with a reconstructed 3D model of brain activity by mapping touch display movements to rotation in one dimension.

2.2 Experimental setup

Eight male volunteers from the Technical University of Denmark, between the ages of 26 and 53 (mean age 32,75 years) participated in the experiment. Replicating the setup for identifying neural correlates of emotional responses triggered by affective pictures, originally performed using a high density 129 electrode array [3], we in the present study applied a simplified approach based on a portable wireless Emotiv Research Edition 14 channel neuroheadset (http://emotiv.com) to capture the signal from Ag/AgCl electrodes positioned at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 according to the international 10-20 system. Channels were recorded at a sampling rate of 128Hz. using the electrodes P3/P4 as CMS reference and DRL feedback respectively. Based on earlier studies showing that late emotional responses to affective pictures remain unaffected when varying the size of images [11], the participants viewed a randomized sequence of 60 IAPS images presented on the 3.5" display (800 x 480 screen resolution) of N900 Nokia smartphones rather than on a standard monitor. Combining earlier experimental designs for eliciting emotional responses when viewing affective pictures, we selected 3 x 20 images from the user rated international affective picture system IAPS [5] identical to the subset used in [3] representing categories of pleasant (erotic and family photos) unpleasant (mutilated bodies, snakes and spiders) and neutral images (simple objects as well non-expressive portraits of people). Taking into consideration findings establishing that the ERP neural correlates of affective content in images can be distinguished even when

the exposure of target pictures are limited to 120ms [6], we opted for adopting the experimental picture viewing paradigm outlined in [12], where a randomized sequence of images from the 3 x 20 IAPS picture categories are presented with 0.5 second prestimulus consisting of a white fixation cross on black background, before a 1 second visual stimulus presentation of a picture followed by a subsequent 1 second poststimulus black screen.

2.3 ICA data analysis

While the rows of the matrix of EEG data initially consist of voltage differences measured over time between each electrode and the reference channel, they come to represent temporally independent events that are spatially filtered from the channel data by applying ICA independent component analysis [13]. Even though neither the location of electrodes or aspects of volume conductance in the brain are part of the equation, the ICA decomposition of the original data matrix often results in independent components resembling scalp projections of brain dipoles, as they reflect synchronous brain activity of local field potentials projected through volume conduction throughout the scalp [14]. However part of the recorded potentials are induced by eye movement, muscle activity and noise and we followed the approach in [15] to cluser ICA components retrieved from each subject to remove the artifacts and isolate the components representing information sources based on the EEGLAB plug-in (v9.0.4.4) for Matlab (R2010b). Initially by reducing the dimensionality of the feature space to N=10 by applying PCA principal component analysis [16], which as a pre-clustering function computes a vector for each component to define normalized distances in a subspace representing the largest covariances within scalp maps and power spectra. Subsequently, we applied a Kmeans algorithm choosing K=10 to cluster similar ICA components and separate outliers that remain more than three standard deviations removed from any cluster centroids. After clustering the 8 x 14 ICA components generated from the continuous EEG trial data of each subject, we after visual inspection of averaged scalp topographies and power spectra manually removed 5 of the 10 clusters, containing spatially localized components like eye artifacts or independent components resembling muscle activity characterized by high power spectra at high frequencies.

2.4 Source reconstruction

The inverse problem of estimating the distribution of underlying sources from a scalp map is severely ill-posed with multiple solutions, as the electrodes are placed at a distance and therefore sum the volume conducted brain activities from cortical areas throughout the scalp [15].We note that apart from providing a relevant neurofeedback signal it has been argued that a sparse 3D representation may in fact also improve decoding [17]. The forward propagation is linear and written in terms of a matrix A, relating the measured electrode signals $Y = AX + E$ to the sought source signals X where E is a noise term [18]. The forward model depends on sensor positions based on a head model of

the spatial distribution of tissue and conductivity values. Assuming the noise to be time independent Gaussian distributed, the observation model becomes $p(y_t|x_t, \Sigma_E) = N(y_t|Ax_t, \Sigma_E)$ where Σ_E is the noise spatial covariance matrix. We here apply a Bayesian formulation of the widely used minimum norm (MN) method for solving the inverse problem [19]. The MN method allows for fast computation of the inverse solution. In a MN setting a multivariate Gaussian prior for the sources with zero mean and covariance $\alpha^{-1}I_{N_d}$ is assumed. Moreover, it is assumed that the forward propagation model is fixed and known. With Bayes rule the posterior distribution is maximized by

$$\mathbf{\Sigma_y} = (\alpha^{-1}\mathbf{A}\mathbf{A}^T + \beta^{-1}\mathbf{I}_{N_c})^{-1} \tag{1}$$

$$\hat{\mathbf{X}} = \alpha^{-1}\mathbf{A}^T\mathbf{\Sigma_y}\mathbf{Y} \tag{2}$$

where the hyper parameters, α and β are estimated online using a Bayesian EM approach.

3 Results

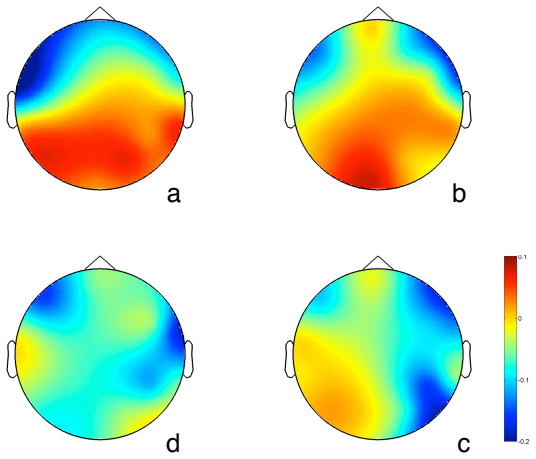

Fig. 2. Mobile EEG event related potentials ERP averaged across eight subjects at 300-500ms after stimuli in the 8-12 Hz frequency band, captured by a 14 channel wireless neuroheadset when viewing affective images on the 3.5" display of a smartphone depicting: a) pleasant - erotic couples b) unpleasant - mutilated bodies c) neutral people and d) household objects. Compared to earlier neuroimaging findings based on the same paradigm but using high density 129 electrode EEG equipment in a laboratory setting [3] [6] we obtain similar results indicating: overall increased posterior activation for a) pleasant and b) unpleasant compared to c) neutral people and d) objects, as well as increased activation in parietal cortex for a) pleasant versus b) unpleasant content.

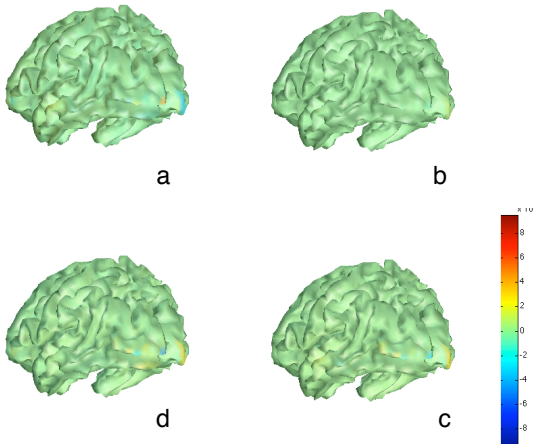

Fig. 3. Activation at 172ms after picture onset in the 8-12Hz frequency band may represent the 150-200ms early posterior negativity EPN previously observed [3] [6] based on reconstruction of sources generated from scalp maps averaged across eight subjects viewing: a) pleasant b) unpleasant c) neutral people and d) objects. Consistent with earlier neuroimaging findings, the reconstructed sources reflect increased activity in the 150-200ms time window for a) pleasant versus b) unpleasant, whereas the differences between pleasant a) versus c) and d) neutral content appear less significant.

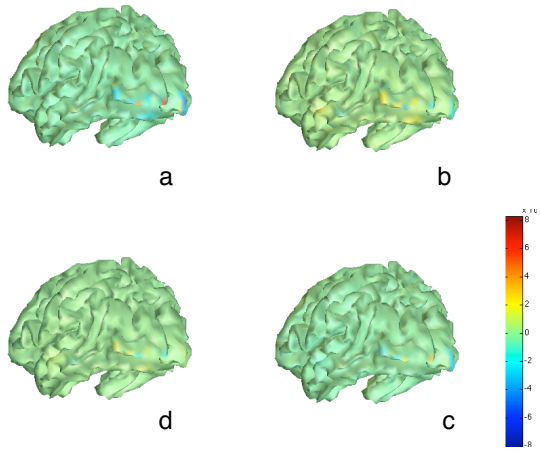

Fig. 4. Activation at 422ms after picture onset in the 8-12Hz frequency band may represent the 300-500ms late posterior positivity LPP previously observed [3] [6] based on reconstruction of sources generated from scalp maps averaged across eight subjects viewing: a) pleasant b) unpleasant c) neutral people and d) objects. Consistent with earlier neuroimaging findings, the reconstructed sources reflect increased activity and polarity reversals in the 300-500ms time window for a) pleasant versus b) unpleasant, and increased activity for affective versus c) and d) neutral content.

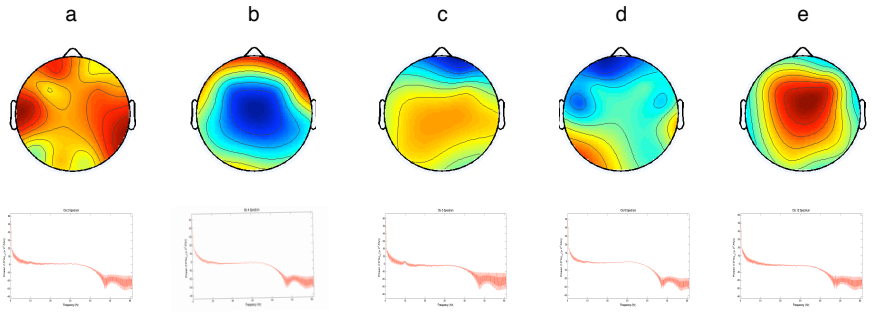

Fig. 5. Clusters of scalp maps and associated power spectra generated from continuous mobile EEG trial data from eight subjects, by applying a kmeans algorithm to 8 x 14 temporally independent ICA independent components represented in a 10 dimensional subspace reduced by PCA principal component analysis. While the clustered ICA components do not represent absolute scalp map polarities as such, they indicate common sources of synchronous brain activity in the 8-12 Hz frequency band, consistent with activities in central, temporal and parietal cortex previously observed to differentiate responses when viewing affective pictures compared to neutral content [3] [6].

4 Discussion

Combining a 14 channel neuroheadset with a smartphone for capture and processing of brain imaging data, our findings indicate we can distinguish among emotional responses reflected in different scalp potentials when viewing pleasant and unpleasant pictures and thereby replicate results previously obtained using conventional high density 129 electrode EEG equipment [3] [6]. Analyzing the event related potentials ERP averaged across eight subjects at 300-500ms after stimuli in the 8-12 Hz frequency band when viewing affective images (Fig.2), we find overall increased posterior activation for pleasant and unpleasant pictures compared to neutral people and objects, as well as increased activation in parietal cortex for pleasant versus unpleasant content. Illustrating how varying emotional intensity in the 300-500ms time window after presentation of emotional content draws attention and defines a selective processing making it possible to distinguish among the feelings triggered when consuming media in a real life setting.

Even though the neuroheadset has only a limited number of channels and no central electrodes, its inclusion of positions F7/F8, P7/P8 and O1/O2 are likely essential for the obtained results, as these electrodes have erlier been shown to contribute significantly to the differentiation between affective and neutral pictures using conventional EEG equipment [3]. Raising the question as to whether the electrode positions can be considered similar, as the form factor of the neuroheadset will provide a slightly different fit for each subject depending on the shape of the head in contrast to traditional EEG caps. However, even when

electrodes are accurately placed the recorded potentials may still vary due to individual differences in cortical surface and volume conduction. We therefore clustered the 8 x 14 ICA components generated from continuous EEG trial data in order to identify common patterns of brain activity across the eight subjects. Among the clusters retained after artifact removal (Fig.5), 39 ICA components clustered in b) and d) were shared by all eight subjects, the 18 ICA components within clusters a) and e) by five subjects, while c) was related to 7 ICA components found in three subjects. Indicating an ability to consistently capture common patterns of brain activity across subjects even when taking into account the less accurate positioning and limited number of electrodes. While the clustered ICA components do not represent absolute scalp map polarities as such, they indicate common sources of synchronous brain activity in the 8-12 Hz frequency band, consistent with activities in central, temporal and parietal cortex previously observed to differentiate responses when viewing affective pictures compared to neutral content [3] [6].

Going beyond analysis of averaged ERPs and clustering of ICA components, we took a Bayesian approach to learn the parameters for applying the minimum norm (MN) method and thus reconstruct the underlying sources from the recorded scalp potentials. Initially exploring the 150-200ms time window an activation at 172ms after picture onset in the 8-12Hz frequency band may represent the early posterior negativity EPN previously observed [3] [6] here based on reconstruction of sources generated from scalp maps averaged across eight subjects viewing: a) pleasant b) unpleasant c) neutral people and d) objects. Consistent with earlier neuroimaging findings, the reconstructed sources reflect increased activity in the 150-200ms time window for pleasant versus unpleasant, whereas the differences between pleasant versus neutral content appear less significant. This early component thought to reflect direction of attentional resources has earlier been found to be more significant for pleasant relative to neutral content, and source reconstruction may thus potentially provide additional features for differentiating among positive and negative content. Within the 300-500ms time window we found a maximal activation at 422ms after picture onset which based on the reconstructed sources may represent the late posterior positivity LPP previously observed using a conventional EEG setup [3] [6]. It has been suggested that the LPP component reflects increased allocation of neural resources for processing emotionally salient relative to neutral content, which here appear activated in the left parietal cortex for pleasant versus unpleasant, and increased activity for affective versus neutral content. Applying a Bayesian formulation to reconstruct the underlying neural sources may thus provide additional information that not only adds to the differentiation of emotional responses captured in a mobile EEG setting, but may also provide an intuitive interface for interacting with a 3D rendered model of brain activity as a basis for developing novel bio-feedback applications. (Fig.1).

The early and late components are not limited to differentiating among the stark emotional contrasts characterizing images selected from the IAPS collection [5]. Whether we read a word with affective connotations, come across some-

thing similar in an image or recognize from the facial expression that somebody looks sad, the electrophysical patterns reflecting the connections among neural populations in the brain seem to suggest that the underlying emotional processes might be the same [20]. Reflecting that we are constantly attracted to or avoiding sensations related to traces in memories capturing pleasure and pain of past experiences, that as feelings are conceptualized as bodily states integral to establishing our sense of self [21]. Using fMRI imaging in experiments to trace which parts of the brain are involved when people read emotional words, the results indicate that activation in two distinct neural networks are linearly correlated with the values of valence or arousal [22]. Overall the valence network linking prefrontal areas and the amygdala are activated in a reciprocal manner whenever the emotional balance shifts from positive to negative, suggesting a feedback loop that moderate our feelings in order for them not to grow out of bounds. Whereas the amount of arousal in words are positively correlated with increased neural activity in a circuit involving the cingulate cortices and the hippocampus linked to prefrontal areas that might again provide an inhibiting effect on arousal. Meaning that the our responses to the emotional content we come across in images or words as measured in the IAPS [5] and ANEW [23] user rated values framed by the dimensions of valence and arousal, might literally correspond to actual neural processes in the brain pertaining to two distinct networks. The ability to continuously capture these patterns by integrating wireless EEG sets with smartphones for runtime processing of brain imaging data may offer completely new opportunities for modeling the mental state of users in real life scenarios as well as providing a basis for novel bio-feedback applications.

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